A NOVEL MULTI PARAMETERIZED MODIFIED LOCAL BINARY PATTERN FOR LUNG CANCER DETECTION BY MACHINE LEARNING METHODS

PhD Synopsis submitted to CHRIST (Deemed to be University) as partial requirement for the award of the Degree of

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IN
COMPUTER SCIENCE AND ENGINEERING

by

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ABSTRACT

It has been proved that the Lung Cancer diagnosis seems to be difficult and the survival rate is less than twelve months. Therefore we need a system which can be easily identified from the CT images or similar kinds of images where prediagnosis is easily done. In the first part of the research was to identify the malignant and normal cells from the CT images collected from various medical colleges across India. A classification model was developed with Better accuracy. Here the Modified Local Binary pattern has given better accuracy. Evaluation had been done on the results acquired and found the result were valid and appropriate. In the second part of the research was conducted by integrating the selected Image features, Risk factor and to Identified the Patients with symptoms of high risk to low risk lung cancer. Integration using feature selection produced intended result. Modified Principal component analysis (PCA) produced largest possible variance and each succeeding component in turn has the highest variance possible. The modified Principal Component Analysis had been proved to be more accurate compared to the Normal principal component analysis. In third part of the research 2D images were converted into a 3D image. The 3D image shows the exact location of the Lung cancer by 4D visualization and 3D rotation, thus giving better clarity to the existing 2D images. The research outcomes are; Classification of the existing 2D Lung Images into Malignant and benign, Integrating various parameters related to Lung Cancer to identify if a person is having Lung Cancer or Normal and finally converting the 2D images into 3D rotation so as to get clarity on the existing 2D images. The conversion from 2D to 3D produced better clarity in the image and produced a rotation with 4D matrix, which in turn developed 3D image on the existing 2D image.

Key words: Lung Cancer, Deep Learning, CT scan, Gini Index, Confusion Matrix

1. INTRODUCTION

The research was conducted by introducing the Lung Cancer prevalence as how it affect to human. The causes, survival rate and finally need of early detection was thoroughly studied. The study was carried out to understand the Diagnosis measures like, pathological test and various image scan available at present like X-ray images, Computed Tomography images(CT), PET scan images etc.

The first part of the research was to identify the malignant and normal cells from the CT images collected from various medical colleges across India. The images were of Dicom format. The Methodology used here was a Classification model, developed from 2D images with improved efficiency compared to all the previous works available.

An image preprocessing was done by using Median filter, Gabor filter and watershed segmentation and processing was done by Zero component whitening, Modified Local Binary pattern and LESH Vector were developed. Deep learning methods to differentiates the malignant and normal cells with Training data set (20,000 images from Hospital) and Sample Data set(32 characteristic features samples with Lung cancer nodules). A classification model was developed with Better accuracy to differentiate the Malignant and Normal cells.

The second part of the research was conducted by integrating the selected; A) Image features, B) Risk factor and C) Symptoms of Lung Cancer related data to identify the Lung Cancer. The Purpose of the study was to identify the Patients with symptoms of high risk to low risk Lung Cancer. Integration using feature selection produced intended result.

Modified Principal component analysis (PCA) produced largest possible variance and each succeeding component in turn has the highest variance possible. The result of modified PCA and LDA reduced the run time and increased the Accuracy of the results. Identified the Patients with symptoms of high risk to low risk Lung Cancer.

The third part of the research that were to convert into a 3D image. The 3D image shows the exact location of the Lung cancer nodule in the CT images. Conversion from 2D to 3D produced better clarity in the Lung Cancer nodule. Z- Axis can divide the body into superior

and inferior parts with axial plane therefore, this is better used here to identify Z-gap, which is in multiple CT scan the gap between each slice.

The need, motivation and scope of the research are explained in the below sections.

2. LITERATURE REVIEW

Lung Cancer disease is causing more than one million deaths all over the world regularly. It constitutes 13% of all new cases of cancer growth and 19% of deaths due to disease worldwide. Two million new cases of Lung disease were estimated to occur in 2022. In India, Lung malignancy constitutes 6.9% of all new illnesses and 9.3% of all cancer related tumours in both sexes, along with the associated death rate the disease most commonly amongst men[1].Proper care could improve survival rates[1]. Lung Cancer development varies according to geographic region and ethnicity. A general Lung Cancer rate development of 5 years of durability is about 15 percent in developed nations and 5 percent in developing nations. Low portion of computer tomography (CT) screening in high-risk populations showed a relative drop in growth mortality of 20 percent in Lung Cancer, but with a false positive 96 percent result[1].

2.1 Approaches

Lung Cancer is the most common cancer in the world and leading cause of death from cancer, with around 1.8 million new cases and 1.6 million deaths in 2012[2-5]. Lung Cancer's five-year survival rate is 13–15 per cent[6]. The late stage diagnosis of Lung Cancer is the determinant factor for high disease mortality. This is explained mainly by lung to central nervous system metastases, as seen in 54 percent of cases[7-12].

Lung Cancer is a malignant lung tumor developed by the bronchial epithelium, bronchioles, alveoli, and bronchial mucosa. Such post-operative procedures include relapses, metastasis and a number of forms of histology. In 2015, the classification of Lung tumors was published by the World Health Organization (WHO)[13]. Lung Cancer's two primary forms are tiny pulmonary carcinoma (SCLC), and non small pulmonary carcinoma (NSCLC). NSCLC accounts for 80 per cent of all cases of Lung Cancer with distinct molecular biological features and disease variants in clinical course[13,14]: Adenoquamous, adenocarcinoma, carcinoma of squamous cells, carcinoma of large cells and neuroendocrine carcinoma of large cells. In other NSCLC subtypes, adenocarcinoma originates from the

bronchial mucosa's glandular cells, and is also the main histological subtype of other types of Lung Cancer.[14-16]

2.2 Challenges

Different therapeutic approaches require that specific histological forms of Lung Cancer and their molecular subtypes be identified. It was found that the condensate content of patients with Lung Cancer varies from that of healthy individuals, Nevertheless, no unique biomarkers of the proteins were found. Similarly, unique markers need to be investigated as one of the most enticing non-invasive sources of Lung Cancer biomarkers in the spinal cord[17-20]. The medical image classification algorithm that combines the extraction of elevated components from a coding scheme with custom image highlights, known as CNMP. In addition, the effect of image increasing on the accuracy and running time of the algorithm[19-30].

Area of Research	Methodologies	Research Gaps Identified
Classification from 2D CT images	• Assessment of the impact of disease and treatment to adjacent Organs. • Automate processes in the initial interpretation of images and integrating with the clinical workflow to reduce the diagnosis time	Integration and selection of image features with symptoms and risk factors could be incorporated in the framework development along with the clinical diagnosis
	• Early detection and correct diagnosis . • Deep learning models perform better in lung cancer diagnosis •	The research study is based on the biopsy specimen, which could be extended to the image Image features – 2D & 3D
	• Detection of aging biomarkers • Personalized anti-aging therapy • Brain-computer interfaces • Integrated AI assistants	Weak to Super Intelligence based AI could be used in the early diagnosis phase of Lung cancer prediction
	• Performance of machine learning classification schemes • Prediction of post-operative life expectancy • Knowledge discovery in databases • Cluster Analysis	ANN MLP based classification has given around 82% efficiency. Extending to Deep learning approaches could be tried to improve the performance
	• Performance of machine learning classification schemes • Prediction of post-operative life expectancy • Knowledge discovery in databases • Cluster Analysis	ANN MLP based classification has given around 82% efficiency. Extending to Deep learning approaches could be tried to improve the performance
	• Detection of aging biomarkers • Improving the life expectancy by adopting advanced AI techniques	Weak to Super Intelligence based AI could be used in the early diagnosis phase of Lung cancer prediction

	• Early detection and correct diagnosis . • Deep learning models perform better in lung cancer diagnosis • Deep learning models give reasonable AUC from 0.8810 to 0.9119	The research study is based on the biopsy specimen of SCLC, NSCLC which could be extended to the image Image features – 2D & 3D
	• Assessment of the impact of disease and treatment to adjacent Organs.	Integration and selection of image features with symptoms and risk factors could be incorporated
tegrating image features, risk factors and symptoms.	• Detected indeterminate pulmonary nodules • Lung cancer prediction using machine learning and advanced imaging techniques	Classification Model with CAD for CNN can be extended to integration of 2D and 3D image scans
	• Median-supplement methods to identify hormonal and HER2 receptor status phenotypes using gene expression profiles • Median-supplement methods perform better than the traditional machine learning methods	Improving precision by including image features of *2D & 3 D scans*
	• The Survival Causal Tree • Discover patient subgroups with heterogeneous treatment effects from censored observational data	Focus is on post diagnosis environment: This approach could be integrated for the early diagnosis phase of Heterogeneous classification models in a CAD Frame work.
	• Texture analysis involves the mathematic processing of medical images to derive sets of numeric quantities that measure heterogeneity.	Integration and selection of heterogeneity can be extended to deep learning methods.
onversion of 2D to 3D image	• The visual aspects of the density changes • This proves that even in lesions that appear stable, a change in density occurs	Statistical tool can be extended to 3D image features.
	• A new quantitative image feature analysis scheme • A quantitative image feature-based classifier is better than a genomic biomarker-based classifier	Ensemble of classifiers approach could be used, by including non-clinical parameters during the early detection phase
	• Texture analysis involves the mathematic processing of medical images to derive sets of numeric quantities that measure heterogeneity.	Integration and selection of heterogeneity can be extended to deep learning methods.
	• Detected indeterminate pulmonary nodules • Lung cancer prediction using machine learning and advanced imaging techniques	Classification Model with CAD for CNN can be extended to integration of 2D and 3D image scans
	• The Survival Causal Tree • Discover patient subgroups with heterogeneous treatment effects from censored observational data	Focus is on post diagnosis environment: This approach could be integrated for the early diagnosis phase of heterogeneous classification models in a CAD Frame work.
	• Median-supplement methods to identify hormonal and HER2 receptor status phenotypes	Improving precision by including image features of *2D & 3 D scans*

	using gene expression profiles • Median-supplement methods perform better than the • traditional machine learning methods	
	• A quantitative image feature-based classifier is better than a genomic biomarker-based classifier	Ensemble of classifiers approach could be used, by including non-clinical parameters during the early detection phase
	• The visual aspects of the density changes • This proves that even in lesions that appear stable, a change in density occurs	Statistical tool can be extended to 3D image features.

Table 1. A Tabular format of Journal Referred

3. THE RESEARCH GAP AND CHALLENGES

The key research gaps identified are as follows:

- The existing methods fail in many situations to provide adequate and proper identification of Lung Cancer from 2D images. The inaccurate prognosis of Lung Cancer is largely due to the inconsistency in analyzing pulmonary nodules.
- The literature review highlights the need for Lung Cancer prediction models that integrates image features, symptoms and risk factors to improve the overall accuracy of CAD systems.
- The study brings out the requirement of novel deep learning models that integrates heterogeneous inputs such as Image features, Risk factors and Symptoms.
- The existing models underperform in differentiating the nature of pulmonary nodules located in CT scans.

The key challenges:

- Detection of exact pulmonary nodules in Lungs images.
- Selection of principal components from the features of Lung Cancer.
- Accurate detection of malignant nodules from CT images.
- Design of a model for combining heterogeneous inputs and forming the most discriminative feature vector for Lung Cancer detection and classification.
- Design of a deep learning model with heterogeneous inputs for Lung Cancer detection and classification.

4. PROBLEM STATEMENT

To develop a frame work for Lung Cancer Classification by integrating the selected Image features, Symptoms and Risk factors using machine learning methods.

5. OBJECTIVES

1. To develop a new model for Lung Cancer detection and classification from 2D CT images
2. To design a model for Lung Cancer detection and classification by integrating image features risk factors and symptoms.
3. To devise an algorithm for classification of Lung Cancer from 3D images.

6. METHODOLOGIES AND TOOLS

Software and Hardware Requirements

Software used

Matlab 19R

Hardware Used

- ✓ The HP Z6 Workstation
- ✓ Xeon Scalable Gen 2 and Gen 2 Refresh processors support 2933MHz memory.
- ✓ NVIDIA Quadro GP100 16GB
- ✓ Blackmagic Design Decklink 8K Pro - 8K Capture & Playback Card
- ✓ Load Operating System on M.2 Drive 1

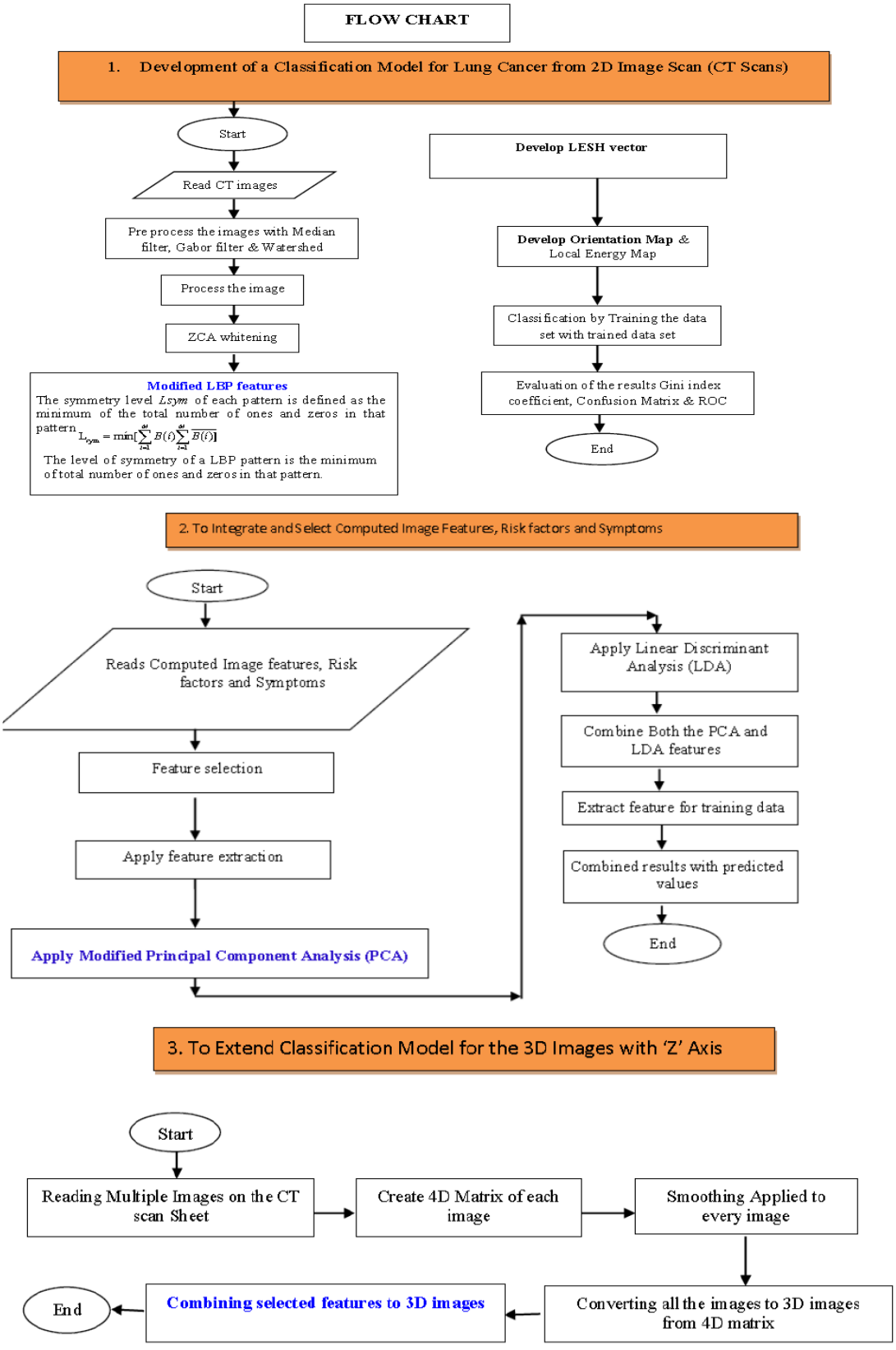
FLOW CHART
1. Development of a Classification Model for Lung Cancer from 2D Image Scan (CT Scans)
Start
Read CT images
Pre process the images with Median filter, Gabor filter & Watershed
Process the image
ZCA whitening
Modified LBP features
The symmetry level Lsym of each pattern is defined as the minimum of the total number of ones and zeros in that pattern
$L_{sym} = \min[\sum_{i=1}^{di} B(i) \sum_{i=1}^{di} \overline{B(i)}]$
The level of symmetry of a LBP pattern is the minimum of total number of ones and zeros in that pattern.
Develop LESH vector
Develop Orientation Map & Local Energy Map
Classification by Training the data set with trained data set
Evaluation of the results Gini index coefficient, Confusion Matrix & ROC
End
2. To Integrate and Select Computed Image Features, Risk factors and Symptoms
Start
Reads Computed Image features, Risk factors and Symptoms
Feature selection
Apply feature extraction
Apply Modified Principal Component Analysis (PCA)
Apply Linear Discriminant Analysis (LDA)
Combine Both the PCA and LDA features
Extract feature for training data
Combined results with predicted values
End
3. To Extend Classification Model for the 3D Images with 'Z' Axis
Start
Reading Multiple Images on the CT scan Sheet
Create 4D Matrix of each image
Smoothing Applied to every image
Converting all the images to 3D images from 4D matrix
Combining selected features to 3D images
End

Fig.1. Flow chart of research work carried out

7. A MATHEMATICAL MODEL TO EXPLORE THE DETAILS IN AN IMAGE WITH LOCAL BINARY PATTERN DISTRIBUTION (LBP)

Local details pattern

From a given image, the pattern of the details distributed around has been studied by several researchers. Recognizing the pattern of distribution of details around a pixel has been studied local binary pattern distribution (LBP). In LBP, we scan all the, neighboring pixels and find out where each of the eight neighbors has large, value than the pixel itself. This is represented as a binary number and the vector of size 8. By processing this vector, we study the pattern of the image.

In our research we extended this study as follows:

1. Instead of binary values, we capture the actual increase of the value from the value at the home pixel.
2. We extended the neighbourhood upto K distance and aggregate the behavior of the neighbours when compared to the home pixel.

The above extention enriches the study of the pattern. The local details pattern (LDP) approach consists of three phased:

Phase 1: Local Detail Analysis.

In this phase, we consider the *k* neighbors of the home pixels in all the eight directions and aggregate the values. This produces the Local details vector $L(x)= [l_1,l_2,.....,l_7]^T$ where each l_i is a number.

Phase 2 : Identify the Direction of Growth

In this phase we convert the local details vector *L(x)* into a probability density function which proposes the probability that the growth is in a particular direction (for Eight Direction). We use soft max function $P(i) = \frac{e^{r_i}}{\sum_{i=0}^{7} e^{r_i}}$ ……(1) to evaluate the *pdf*.

The result of this Phase is a *pdf* of eight directions

$P(x)=(P_0, P_1, P_2, P_3, P_4, P_5, P_6, P_7)$

Where P_i = Probability that the growth is in direction *i*.

Phase 3: Validation of the pdf

In this phase we validate if the *pdf* gives a meaningful guidance for the decision making in identifying the growth direction. Note that a *pdf* need not always gives a meaningful guidance. If all the probabilities are same, there is no guidance at all.

We use the mathematical tool entropy to accomplish the task of validation. The entropy of a *pdf* $p = (P_0, P_1, \ldots\ldots P_{d-1})$ is defined by $H(p) = -\sum_{i=0}^{d-1} P_i \log_2 p_i$ .....(2)

when the entropy is small, the pdf gives a meaningful guidance.

Phase 4: Confirmation of the Directions

If the *pdf* is worth considering for guidance, we move in the guided direction, choose the neighboring pixel x^i and find the LDP vector and the corresponding *pdf*.

Now we have two *pdf.*

The *pdf p(x)* is the *pdf* of the home pixel *x*.

The *pdf* $p(x')$ is th *pdf* of the neighbor pixel *x'*.

Note that phase 3 has recommended the growth direction $x \to x'$.

We use cross entropy to verify if *p(x)* and *p(x')* are confirming the pattern. The cross entropy of two *pdf p* and *p'* is defined as

$$H(p, p') = -\sum_{i=0}^{d-1} P_i \log_2 p_i' \quad \text{.....(3)}$$

when the cross entropy is small, they confirm the direction. In case the cross entropy values is high, the growth direction is not consistant. The overall approach is shown in the flowchart.

This model shows how local binary pattern can be efficiently manipulated. Here, Instead of binary values, the values that are of home pixel is taken into account for the research. We extended the neighbourhood upto K distance and aggregate the behavior of the neighbours when compared to the home pixel. Thus we could get a higher the cross-entropy, where, poor the correlation between the guidance.

8. Development of a classification model Based on the 2D image scans

This part of the research had been generating a classification model for CT images using the data after image processing followed by image preprocessing. The images are preprocesses and processed, thus the goal here is to detect correctly pulmonary nodules to recognize and screen Lung Cancer patient.

Preprocessing

The collected images differ in its size and shape hence, resized them into 128*128 pixels. The images are again converted to grayscale images. The pre-processing is done with smoothening of images, enhancement of images and finally segmentation as well with Gabor filter, Median filter and watershed segmentation. Noise detected in the CT images & comparison with various filters. The following are the noise I encountered during the preprocessing; Slice thickness, Patient size, Noise metrics, Texture, Non-uniformity. The filters I have used are Median filters and Gabor filters along with watershed segmentation

The comparison as follows: Additive white Gaussian noise (AWGN), Mean-square error (MSE), Peak signal-to-noise, ratio (PSNR), Structural similarity index measure (SSIM)

Noise Type /Filters	**PSNR**	**MSE**	**Energy Ratio**	**MAXERR**	**SSIM**
Speckle Noisy Image	25.6057	178.8594	0.9928	43	0.0100
Median Filter Output Image	**34.7976**	**177.5321**	**1.0213**	**198**	**0.6901**
Gabor Filter Output image	33.1563	99.9928	1.0105	198	0.7024
Chebyshev filter Output image	32.8493	219.1137	1.0213	143	0.7457
Butterworth filter Output image	29.8782	177.5321	1.0301	166	0.6795
Bessel filter Output image	31.733	197.7658	1.0213	98	0.6901
Elliptic filter Output image	23.5555	96.9928	1.0105	69	0.7024
Low-pass filter Output image	22.7654	279.8137	1.0213	113	0.7457
High-pass filter Output image	29.1182	168.531	1.0301	178	0.6795
Band-pass filter Output image	24.8776	98.756	1.0213	88	0.6901
Band-stop filter Output image	24.7176	137.0321	1.0213	58	0.6901
Notch filter Output image	23.1562	123.6908	1.0105	89	0.7024

Comb filter Output image	22.8113	169.1137	1.0213	123	0.7457
All-pass filter Output image	29.3252	137.768	1.0301	118	0.6795

Table 2. Comparison of filter parameters for speckle noise

Noise Type /Filters	**PSNR**	**MSE**	**Energy Ratio**	**MAXERR**	**SSIM**
AWGN	28.0991	100.7331	0.9946	44.3551	0.6325
Median Filter Output image	35.5768	143.5727	1.0131	192.9070	0.7770
Gabor Filter Output image	**36.4970**	**143.5727**	**1.0131**	**192.9070**	**0.7822**
Chebyshev filter Output image	32.8493	219.1137	1.0213	143.678	0.7457
Butterworth filter Output image	29.8782	177.5321	1.0301	166.455	0.6789
Bessel filter Output image	31.733	197.7658	1.0213	98.666	0.6778
Elliptic filter Output image	23.5555	96.9928	1.0105	69.148	0.2355
Low-pass filter Output image	22.7654	279.8137	1.0213	113.896	0.3421
High-pass filter Output image	29.1182	168.531	1.0301	178.450	0.6543
Band-pass filter Output image	22.8113	169.1137	1.0213	123.988	0.7666
Band-stop filter Output image	24.7176	137.0321	1.0213	58.654	0.6544
Notch filter Output image	23.1562	123.6908	1.0105	89.344	0.7654
Comb filter Output image	23.5555	96.9928	1.0105	69.443	0.7665
All-pass filter Output image	29.3252	137.768	1.0301	118.111	0.3455

Table 3 Comparison of filter parameters of AWGN noise

Zero component analysis (ZCA) Whitening

Whitening transformation is a step to remove redundancy prior to processing. To calculate zero-mean in the matrix of covariances, this processing is required.

Modified LBP Feature (Local Binary Pattern):

In the Modified Local Binary Pattern (LBP) Features with symmetry level scheme is a texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel with a symmetry level scheme for uniform patterns to further reduce the length of LBP feature vectors. It gives the results as binary numbers.

The symmetry level *Lsym* of each pattern is defined as the minimum of the total number of ones and zeros in that pattern

$$L_{sym} = \min[\sum_{i=1}^{M} B(i) \sum_{i=1}^{M} \overline{B(i)}] \quad \text{.....(4)}$$

The level of symmetry of a LBP pattern is the minimum of total number of ones and zeros in that pattern. Symmetry is invariant with respect to rotation by its definition

Uniform pattern is an effective rule to select LBP features, and it has been widely adopted in existing work. The symmetry level *Lsym* of each pattern is defined as the minimum of the total number of ones and zeros in that pattern. For example, *Lsym* of both patterns (00111111)2 and (00011000)2 are 2. The symmetry level is rotation invariant according to the definition. The most symmetric pattern contains the same number of ones and zeros, indicating a symmetric edge, while the patterns with the lowest symmetry level are the ones consisting of only ones or zeros. It is claimed that the patterns with high symmetry level occur more frequently in the images with more discriminative power. This conclusion is supported by experiments: the comparative performance was obtained using only the patterns of high symmetry level, but the length of feature vectors was reduced by a quarter as shown in Table 2.

Author	Feature	Core Matching Algorithm	Reported Accuracy
Ahonen (2019)	$LBP_{8,2}$	Weighted X^2	0.790
Zhang(2018)	Boosting LBP	χ^2	0.979
Zhang (2013)	MHLVP	Histogram Intersection	0.959
Zhang (2011)	LGBPHS	Weighted Histogram Intersection	0.710.
Shan (2009)	LGBP	EPFDA	0.889.
Yao (2015)	LGBPH	CDP-RankBoost	0.970
Chan (1997)	Multi-Scale LBP	LDA	0.711
Tan (2020)	Gabor+LBP	KDCV	0.850
Zhang (2017)	ELGBP (Mag + Pha)	Histogram Intersection	0.960
Denny (2021)	LBP_{Sym}	Modified LBP feature with symmetry level Algorithm	0.989

Table 4. Comparison of modification

LESH Vector

LESH Base Function Extraction for the image of interest is based on the estimation of Local Energy pattern histogram. Specific orientations are used to measure local energies. Local Energy map and orientation Map is developed here.

Deep Learning Methods

Methods of deep learning are commonly used to classify tissues of cancer development. Deep Learning is a method of implementing an artificial neural network for the emulation of the lung nodules with different layers. Deep, neural network layers eliminate different highlights and afterwards offer different degrees of reflection.

Data Set	MLBP_20,000 (.dcm)
Trained Data set	32 (Samples)
Regression Dropouts	0
Epoch	100 of 100
Training finished	Reached final iteration
Elapsed time	11 min 40 sec
Iteration	100 of 100
Iteration per Epoch	1
Maximum Iteration	100
Frequency	1 iteration
Hardware Resource	Single CPU
Learning rate schedule	Piece wise

Tabel. 5. Experimentation details

Training of Data Set

To perform supervised learning, they need two types of data sets:

1. In the **training data set**, they combine the input data with the corresponding expected output.

2. The **test data set** contains data that they will apply to your model. The Lung image dataset contains more than 20,000 images from various medical colleges in India and identified 32 sample nodules of Lung malignancy which constitute the training dataset.

Data Set	MLBP_20,000 (.dcm)
Trained Data set	32 (Samples)
Model	CNN
Classification Model	CNN's Regression Model
Convolution Layer	3
Relu Layers	4
Fully connected layers	10

Table. 6. Result Details

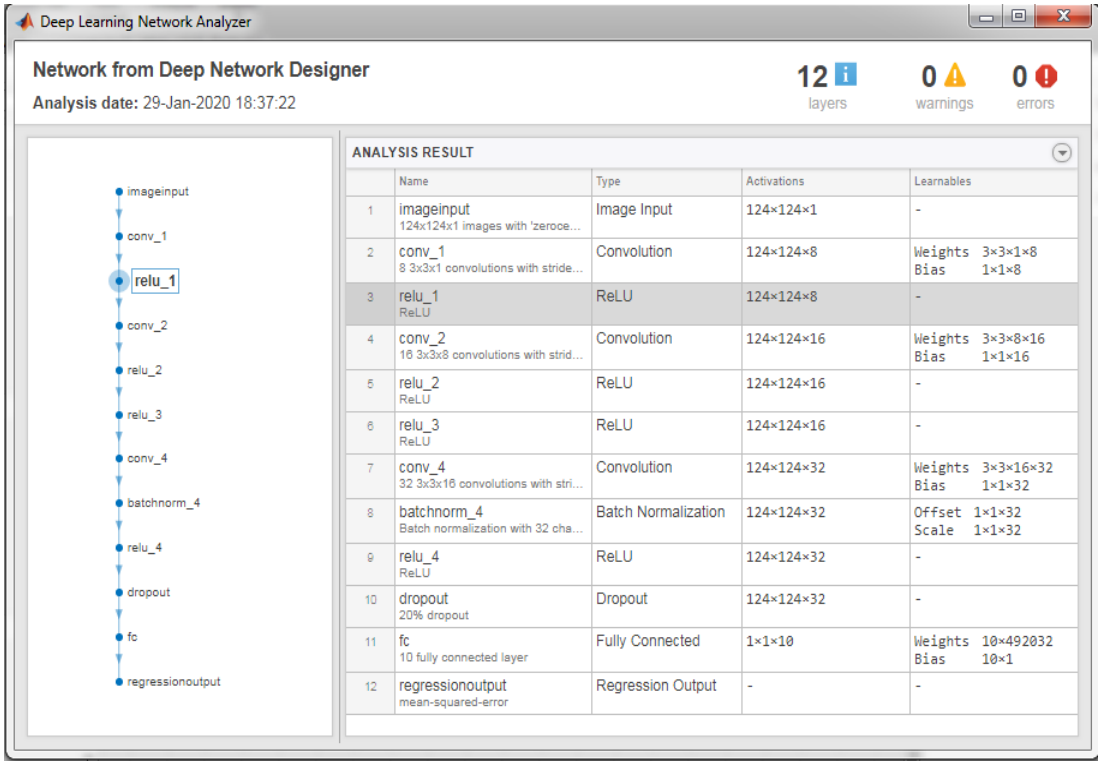
Deep Learning Network Analyzer
Network from Deep Network Designer
Analysis date: 29-Jan-2020 18:37:22
12 layers
0 warnings
0 errors
imageinput
conv_1
relu_1
conv_2
relu_2
relu_3
conv_4
batchnorm_4
relu_4
dropout
fc
regressionoutput
ANALYSIS RESULT
Name
Type
Activations
Learnables
1 imageinput 124x124x1 images with 'zeroce... Image Input 124×124×1 -
2 conv_1 8 3x3x1 convolutions with stride... Convolution 124×124×8 Weights 3×3×1×8 Bias 1×1×8
3 relu_1 ReLU ReLU 124×124×8 -
4 conv_2 16 3x3x8 convolutions with strid... Convolution 124×124×16 Weights 3×3×8×16 Bias 1×1×16
5 relu_2 ReLU ReLU 124×124×16 -
6 relu_3 ReLU ReLU 124×124×16 -
7 conv_4 32 3x3x16 convolutions with stri... Convolution 124×124×32 Weights 3×3×16×32 Bias 1×1×32
8 batchnorm_4 Batch normalization with 32 cha... Batch Normalization 124×124×32 Offset 1×1×32 Scale 1×1×32
9 relu_4 ReLU ReLU 124×124×32 -
10 dropout 20% dropout Dropout 124×124×32 -
11 fc 10 fully connected layer Fully Connected 1×1×10 Weights 10×492032 Bias 10×1
12 regressionoutput mean-squared-error Regression Output - -

Fig 2. Deep learning Network Analyzer

The usage of ReLU helps to prevent the exponential growth in the computation required to operate the neural network. If the CNN scales in size, the computational cost of adding extra ReLUs increases linearly. Our intention of adding 2 Relu layers were only to see the statistical difference.

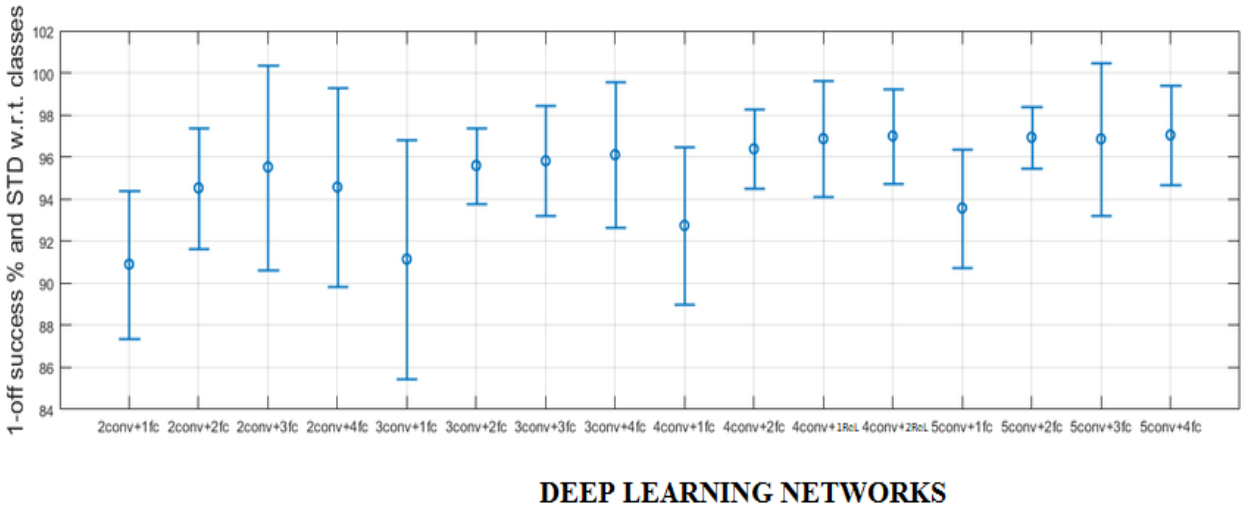

Fig.3. Deep Network Layers at different stages and its corresponding performance analysis(Relu layer with 1 & 2 Layers)

The result shows the accuracy of 97.5% which is comparatively better as of now. Out of this result the Receiver operating characteristic **(**ROC**)** Curve is calculated from true positive and true negative which shows the accuracy of 96%. It is described below with all the details.

Different Algorithms	**Accuracy**
CNN_Regression	93.27
Recurrent Neural Networks (RNNs)	84.22
Long Short-Term Memory Networks (LSTMs)	87.08
Stacked Auto-Encoders	67.07
Deep Boltzmann Machine (DBM)	76.99
Deep Belief Networks (DBN)	90.00
Decision tree	73.12
Random forest	86.44
Gradient-boosted tree	64.22
Multilayer perceptron	85.99
One-vs-Rest	56.32
Naive Bayes	90.01
K-Nearest Neighbor	81.58

Table. 7 Comparison of the Result with Accuracy

Classifiers	**Precision (%)**	**Recall (%)**	**F-Measure**
CNN_Regression	93.27	96.98	97.48
Recurrent Neural Networks (RNNs)	84.22	97.88	93.66
Long Short-Term Memory Networks (LSTMs)	87.08	100	98.475
Stacked Auto-Encoders	67.07	90.385	92.15
Deep Boltzmann Machine (DBM)	76.99	90.291	91.625
Deep Belief Networks (DBN)	90.00	96.842	94.358
Decision tree	73.12	88.35	89.655
Random forest	86.44	80.12	83.88
Gradient-boosted tree	64.22	66.34	62.88
Multilayer perceptron	85.99	84.33	84.87

One-vs-Rest	56.32	55.73	52.87
Naive Bayes	90.01	89.82	91.77
K-Nearest Neighbor	81.58	79.88	80.97

Table. 8 Comparison of the Result with different Classification / Classifier

9. A framework by Integrating the selected computed image features, Symptoms and risk factors for the detection of lung cancer

Here the work is carried out by integrating the selected computed image features, Symptoms and risk factors for CAD prediction of Lung Cancer. After the feature selection step they apply feature extraction technique to extract features for training data. They used PCA (Principal Component Analysis) and LDA (Linear Discriminant Analysis) feature extraction technique. Finally, combine both features and create training data for classification by CNN classification.

Sl.No	SYMPTOMS OF LUNG CANCER	WEIGHT (Assigned by Medical Professionals)
1	Cough that is persistent	0-10
2	Cough that produces blood	0-10
3	Pain in the chest that worsens during coughing,	0-10
4	Laughing or deep breathing Pain at the back that worsens during coughing,	0-10
5	Laughing or deep breathing Pain on the shoulders that worsens during coughing,	0-10
6	Laughing or deep breathing Shortness of breath that comes on suddenly and occurs during everyday activities	0-10
7	Unexplained weight loss	0-10
8	Feeling tired or weak Loss of appetite	0-10
9	Bronchitis or pneumonia that won't go away	0-10
10	Hoarseness or wheezing	0-10
11	Swelling in the face or neck	0-10
12	Difficulty swallowing or pain while swallowing	0-10
13	Changes in the appearance of fingers	0-10
14	Bone pain	0-10
15	Headaches	0-10
16	Dizziness	0-10
17	Limbs	0-10
18	Jaundice	0-10
19	Lumps in the neck or collarbone region	0-10
20	Coughing up blood or rust-colored phlegm	0-10

Table 9. Symptoms o f Lung Cancer

Sl. No	RISK FACTORS OF LUNG CANCER	WEIGHT (Assigned by Medical Professionals)
1	Age	0-10
2	Smokes	0-10
3	Area-Q	0-10
4	Alcohol	0-10
5	Smoking	0-10
6	Second-hand smoke	0-10
7	Radon gas	0-10
8	Asbestos Exposure	0-10
9	Air pollution	0-10
10	Arsenic in Drinking Water	0-10
11	Previous Lung Radiation	0-10
12	Personal or Family History	0-10
13	Painting industry	0-10
14	Bauxite Mining Area	0-10
15	Coal mining area	0-10
16	Smoke from plastic Burning	0-10

Table 10. Risk Factors

Feature Selection and Feature Extraction (Modified Principal Component Analysis)

It is a way to compute the first principal component efficiently is shown in the following pseudo-code, for a data matrix *X* with zero mean, ***without ever computing its covariance***

matrix. The covariance-free approach avoids the np^2 operations of explicitly calculating and storing the covariance matrix X^TX, instead utilizing one of matrix-free methods, for example, based on the function evaluating the product $X^T(X\ r)$ at the cost of $2np$ operations.

r = a random vector of length p

$$r = \frac{r}{|r|}$$

do **c** times:
s = 0 (a vector of length **p**)
for each row $x \in X$

$$s = s + (x.r)x$$

eigen value = $r^T s$
error=|eigen value.r-s|

$$r = \frac{s}{|s|}$$

Exit if error < tolerance
Return eigen value, r

Author	Feature	Reported Accuracy
R. Baumgartner, L. Ryner, W. Richter, R. Summers, M. Jarmasz, R. Somorjai(2019)	fuzzy clustering vs. principal component analysis	FC83.25% PCA < 83%
Keith F. Widaman (1999)	PCA with observed variable dimensionality reduction(VDR)	VDR 86% PCA 81%
Frank Wood(2015)	PCA with projection of collinear data(PCD)	PCD90% PCA 89%
Gooitzen Zwanenburg(2017)	principal component analysis and ANOVA–simultaneous component analysis	ANOVA83% PCA 79%
REBECCA ROGERS ACKERMANN(2018)	A Comparison of Variation Patterns Using Matrix Correlation (MC)and Common Principal Component Analysis	MC 90% PCA 85%
Denny Dominic(2021)	Modified Principal Component Analysis (MPCA), The covariance-free approach avoids the np^2 operations of explicitly calculating and storing the covariance matrix X^TX	PCA 83.254% MPCA 98.3051%

Table 11. Comparison of Algorithm

Linear Discriminant Analysis

It is a dimensionality reduction technique which is commonly used for the supervised classification problems. It is used for modeling differences in groups i.e. separating two or

more classes. It is used to project the features in higher dimension space into a lower dimension space.

Making Predictions with LDA

LDA makes predictions by estimating the probability that a new set of inputs belongs to each class. The class that gets the highest probability is the output class and a prediction is made. The model uses Bayes Theorem to estimate the probabilities.

Classification of the data

Data has been classified using SoftMax classification algorithm which has been already described in the previous objective.

10. Extending the classification model for the 3D images with 'z' axis low resolution images.

The multiple images from the CT scan sheet is used here as the 2D multiple images and read Lung images for creating 3D images. Firstly they have created 4D matrix of Lung images and then smoothing applied on images then combine all images and create 3D image.

Feature Selection

A feature selection algorithm can be seen as the combination of a search technique for proposing new feature subsets, along with an evaluation measure which scores the different feature subsets.

i) Four-Dimensional Matrix

A **four-dimensional matrix** or **4D Matrix** is a mathematical extension of the concept of three-dimensional or 3D space.

Conversion to 4D Matrix

$$R = e^{A} = I + \sin\theta_1 A_1 + 1(1-\cos\theta_1)A_1^{\,2} + (1-\cos\theta_2)A_2^{\,2} \quad \text{.....(5)}$$

is a rotation matrix in E^4, which is generated by Rodrigues' rotation formula, with the set of eigen values

$\{e^{\theta_{1i}}, e^{-\theta_{1i}}, e^{\theta_{2i}}, e^{-\theta_{2i}}\}$.

Also,

$$R = (I + A)(I - A)^{-1} = I + \frac{2\theta_1}{1+\theta_1^2} A_1 + \frac{2\theta_1^2}{1+\theta_1^2} A_1^2 + \frac{2\theta_2}{1+\theta_2^2} A_2 + \frac{2\theta_2^2}{1+\theta_2^2} A_2^2 \quad \text{.....(6)}$$

is a rotation matrix in E^4, which is generated by Cayley's rotation formula

Combining selected features to 3D images

i) Orthogonality and vocabulary

In the three-dimensional, there are three coordinate axes—usually labeled *x*, *y*, and *z*—with each axis orthogonal (i.e. perpendicular) to the other two. The six cardinal directions in this space can be called *up*, *down*, *east*, *west*, *north*, and *south*. Positions along these axes can be called *altitude*, *longitude*, and *latitude*. Lengths measured along these axes can be called *height*, *width*, and *depth*.

ii) Visualization of 4D rotations

Every rotation in 3D space has an invariant axis-line which is unchanged by the rotation. The rotation is completely specified by specifying the axis of rotation and the angle of rotation about that axis. Without loss of generality, this axis may be chosen as the *z*-axis of a Cartesian coordinate system, allowing a simpler visualization of the rotation.

Algorithm for Combining selected features to 3D images

Start

Step.1. Calculate Orthogonality

Start Loop

1. Calculate three coordinate axes—usually labeled x, y, and z—with each axis orthogonal to the other two.

2. Calculate six cardinal directions.

End Loop

Step.2. Visualization of 4D rotations

Start Loop

1. Calculate the axis of rotation and the angle of rotation about those axis .Calculate six cardinal directions.

2. Choose as the z-axis of a Cartesian coordinate system, allowing a simpler visualization of the rotation

3. Make every rotation in 4D space has at least two invariant axis-planes which are left invariant by the rotation and are completely orthogonal

End Loop

End

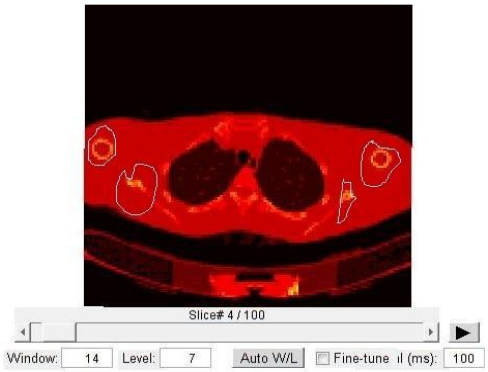

Fig. 4. Image shows the malignant cell in white circled yellow patches

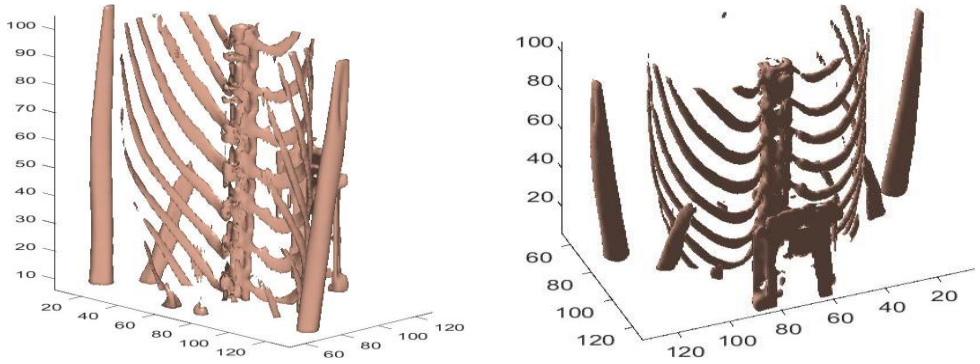

Fig. 5 A & 5 B. 3D image with a general rotation with angular displacements in a ratio of 1:5

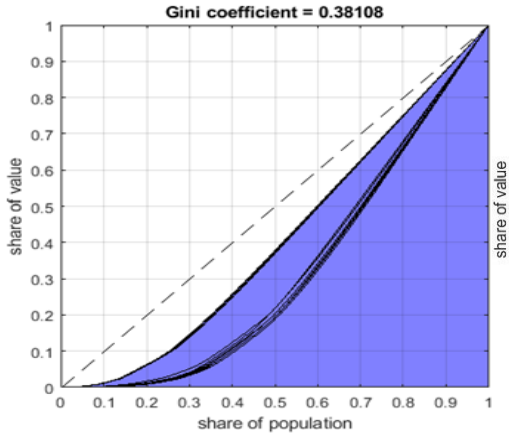

Fig. 6 A. Gini coefficient value from 2D image scan with 0.3818

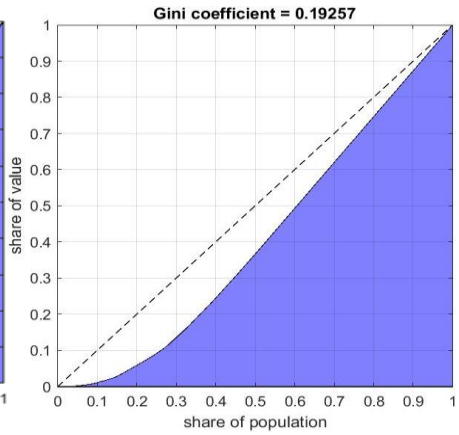

Fig. 6 B. Gini coefficient value after conversion from 2D to 3D image with 0.19257

11. Result and Discussion

The first part of the research work proposes a novel method of classifying images from the 2D image scan for Lung Cancer. ZCA whitening works better with LESH Vector and LBP features, Classification with deep learning methods, better works with Orientation map of LESH vector, Gini coefficient results are useful to identify the images with possible

Occurrence and reduced the runtime as the results itself indicate the variance in the scan and More the Number of layers in classification better the Accuracy. Novelty of this research is that, it improved efficiency by Modified LBP features with 93% accuracy.

In the second part the results identified the Patients with symptoms of high risk to low risk Lung Cancer. It have been calculated using Confusion matrix with True positive value of 96.9%, which indicate that all the selected values where appropriate and there was no throw away attributes. Thus, finally we have the accuracy of 98.3051%. The predicted values from the training of the dataset, which indicate with '0' and '1'. The '1' indicate that the particular person is vulnerable to Lung Cancer and '0' indicate that the person is completely out the danger of the Lung Cancer. Each predicted outcome or confusion matrix represents a point in the ROC space, which gives a final accuracy of 98.214.

In the third part this image shows the exact location of the Cancer cells grown in the Lungs by creating 4D matrix of Lung images and then smoothing applied on images then combine all images and create 3D image. The Result evolved out of the 3D image shows better accuracy in comparison with 2D images scan with 0.19257. Therefore the results show better accuracy after converting them to 3D.

Limitations of my research work

1) Time taken for the data processing may not help in real time analysis,

2) Complexity involved in collecting and processing the heterogeneous data (Normalization errors, perception errors etc)

3) Lack of Bio marker data availability of all patients to make a robust system

12. CONCLUDING REMARKS

The study was conducted by analyzing the 2D images. Developed a classification model to identify the Lung Cancer from 2D image scan with modified LBP features. Integrating the selected image features along with risk factor and symptoms of Lung Cancer related data to predict the Lung Cancer. Developing 3D images from the 2D images, which gave a better Accuracy for the images by Combining Orthogonality and Rotation of the 3D. Mathematical models have been developed based on the information gathered throughout the research.

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LIST OF PUBLICATIONS

PUBLICATION:

1. Denny Dominic and K. Balachandran "Lung Cancer Diagnosis from CT Images Based on Local Energy Based Shape Histogram (LESH) Feature Extration and Pre-processing", ISSN 1876-1100 ISSN 1876-1119 (electronic)Lecture Notes in Electrical Engineering, http://www.springer.com/series/7818, 2020
2. Denny Dominic and K. Balachandran,"A Deep Learning Approach in Early Prediction of Lungs Cancer from the 2D Image Scan with Gini Index", Lecture Notes in Networks and Systems, springer.com/series/15179,2020.
3. Denny Dominic and K. Balachandran, "3D Image Conversion of a Scene from Multiple 2D Images with Background Depth Profile", Algorithms for Intelligent Systems, springer.com/series/16171, 2020.
4. Denny Dominic and K. Balachandran, "Early Prediction of Lungs Cancer by Deep Learning Algorithms from the CT Images with LBP Features", *International Journal of Advanced Science and Technology*, Vol. 29, No.4, (2020), pp. 4200 – 4204.
5. Denny Dominic and K. Balachandran, "Mining Heterogeneous Lung Cancer from Computer Tomography (CT) Scan with the Confusion Matrix ", *Wiley* (Accepted)
6. Denny Dominic and K. Balachandran, " A Proven mathematical Model to explore the details in an image with Local Binary Pattern distribution (LBP)", International Journal of Intelligent Engineering and Systems (Accepted)
7. Denny Dominic and K. Balachandran, "A Novel Method in Mining Heterogeneous Lung Cancer from Computer Tomography (CT) Scan", Journal of Cardiovascular Disease Research (Accepted)